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Robotic Chest-Compression Systems with Real-time Physiologic Feedback: A Systematic Review of Closed-Loop and Machine-Learning Approaches

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Background:

Mechanical chest-compression devices standardize cardiopulmonary resuscitation (CPR), but fixed compression parameters may not match patient physiology. Robotic and algorithm-driven systems that use real-time physiologic signals could enable closed-loop CPR optimization.

Methods:

PubMed was searched from database for clinical, preclinical, and modeling studies evaluating robotic/mechanical chest-compression systems incorporating real-time physiologic feedback (e.g., end-tidal carbon dioxide [$ETCO_2$], arterial pressure, coronary perfusion pressure [CPP], carotid flow) consistent with closed-loop or machine-learning approaches. Eligible studies were synthesized narratively without meta-analysis.

Results:

Five studies met inclusion: two randomized porcine trials, one porcine machine-learning modeling study (n=7), and two simulation/model studies. A closed-loop machine-controlled CPR system sustained higher CPP at 30 minutes versus guideline CPR (22±3 vs 8±3 mmHg) and preserved carotid blood flow during prolonged resuscitation. An AI-driven CPR robot achieved similar hemodynamics to a standard piston device, with no difference in carotid flow (−23.2±20.2 mL/min; P=0.250) and comparable ROSC (83.3% vs 66.7%; P=1.00). Simulation studies suggested that CPP-targeted controllers improved modeled flow/$ETCO_2$, and an ML model predicted carotid flow per compression with high accuracy (R^2=0.96).

Conclusions:

Evidence for physiologic-feedback robotic CPR is limited to preclinical and simulation studies, but supports technical feasibility and potential hemodynamic advantages over fixed-parameter CPR. Human feasibility trials with standardized ventilation, safety outcomes, and neurologic endpoints are required before clinical deployment.

Keywords: Cardiopulmonary resuscitation, Robotics, Closed-loop systems, Machine learning, End-tidal carbon dioxide, Coronary perfusion pressure.

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Introduction

Cardiac arrest remains a leading, time-critical cause of preventable death worldwide, with out-of-hospital cardiac arrest (OHCA) accounting for substantial mortality and long-term neurological disability among survivors. In a global systematic review/meta-analysis of adult OHCA receiving cardiopulmonary resuscitation (CPR), pooled rates were 29.7% for return of spontaneous circulation (ROSC) (95% CI 27.6-31.9), 22.0% for survival to hospital admission (95% CI 18.6-25.7), and 8.8% for survival to hospital discharge (95% CI 7.2-10.6), underscoring the steep attrition across the resuscitation and post-resuscitation continuum [1]. Regional data illustrate even wider variation in outcomes; for example, the Saudi Out-of-Hospital Cardiac Arrest Registry (SOHAR) reported prehospital ROSC of 7.4% and survival to hospital discharge of 2.9%, with good neurological outcome (Cerebral Performance Category 1-3) in <0.5% of cases [2].

These figures highlight a persistent, system-level gap between what is physiologically achievable during resuscitation and what is routinely delivered in real-world settings, particularly where arrests occur at home, response intervals are prolonged, and trained bystander intervention is limited [2]. High-quality CPR is the central modifiable determinant of early survival in cardiac arrest, yet it is difficult to maintain consistently under operational constraints. Manual chest compressions degrade rapidly due to rescuer fatigue, interruptions for rhythm analysis/defibrillation, patient movement, transport logistics, and confined-space challenges, leading to variability in compression depth, rate, recoil, and chest-compression fraction. Mechanical chest-compression devices were developed to standardize compressions and reduce hands-off time, but large randomized and pragmatic trials have not demonstrated clear survival benefit over guideline-based manual CPR in OHCA, despite improved process metrics in selected contexts [4-6]. In addition to uncertain effectiveness, safety concerns persist: a recent systematic review/meta-analysis found manual compressions were associated with a lower risk of compression-related injuries compared with mechanical compressions (OR 0.57, 95% CI 0.46-0.69), while differences in life-threatening injuries were less clear and additional high-quality trials were recommended [7]. Observational in-hospital cardiac arrest (IHCA) data likewise raise concern for confounding by indication and deployment context; one multicenter cohort analysis reported lower odds of survival to discharge (adjusted OR 0.57, 95% CI 0.42-0.77) and lower odds of ROSC (adjusted OR 0.71, 95% CI 0.53-0.95) when mechanical CPR was used compared with manual CPR [8]. Collectively, these findings suggest that "automation of compression delivery" alone is insufficient.

Instead, the next technical frontier is personalization, adapting compressions to the patient's real-time physiology and the dynamic phase of resuscitation. Current resuscitation recommendations still largely operationalize a "one-size-fits-all" approach (fixed targets for depth, rate, recoil, and minimal interruptions), because direct, continuous measurement of perfusion during CPR is rarely available and because evidence for physiologic titration remains heterogeneous [3]. However, the physiologic goals of CPR are fundamentally hemodynamic: maximizing coronary perfusion pressure (CPP), cerebral blood flow, and oxygen delivery while avoiding excessive intrathoracic pressures and trauma. Real-time signals that can serve as perfusion surrogates during CPR include end-tidal carbon dioxide ($ETCO_2$), invasive arterial pressure waveforms (when present), carotid or femoral Doppler flow/velocity, and emerging noninvasive cerebral oximetry and impedance-based

measures. The 2024 International Liaison Committee on Resuscitation (ILCOR) consensus process continues to emphasize implementation science and quality improvement while recognizing the need for innovative approaches that can link CPR delivery to measurable physiologic response [3]. Within this framework, closed-loop control systems, where sensed physiologic variables are continuously fed to an algorithm that adjusts compression parameters, represent a logical evolution beyond manual coaching or simple metronome feedback. Such systems are particularly relevant to complex environments (prehospital transport, catheterization laboratories, emergency departments, and overcrowded wards) where sustained, high-quality compressions and continuous monitoring are challenging but where rapid hemodynamic optimization may yield large marginal gains.

Robotic chest-compression systems with real-time physiologic feedback build on closed-loop principles by integrating (i) actuation (robotic arm/piston platform or mechatronic compression module), (ii) sensing ($ETCO_2$, invasive pressure, Doppler, accelerometry, or multimodal biosignals), and (iii) control logic (rule-based controllers, adaptive control, and machine-learning-enabled policies). Preclinical evidence illustrates feasibility and physiologic promise. A closed-loop, machine-controlled CPR system was designed to optimize CPP during prolonged resuscitation by using real-time hemodynamic feedback to adjust compression/decompression characteristics through machine-learning and control algorithms [9].

Complementing this, hands-free Doppler approaches have been developed to provide continuous carotid blood-flow velocity feedback without interrupting compressions; in a porcine model, a hands-free carotid Doppler system identified compression positions associated with higher time-averaged velocity (range 19-48 cm/s) and corresponding higher peak pressure (50-81 mmHg), versus lower-velocity positions (6-25 cm/s) with lower peak pressure (46-64 mmHg), demonstrating substantial inter-animal variability and suggesting that optimal hand position may be patient-specific rather than fixed [10]. More recently, an artificial-intelligence-driven, biosignal-sensitive robotic chest-compression device was evaluated in a preliminary animal study, further supporting the concept that real-time physiologic signals can be used to modulate compression delivery in an automated platform [11]. Although these studies design are largely preclinical and heterogeneous in design, they converge on a central hypothesis: CPR effectiveness can be improved if compressions are adjusted to the patient's measured perfusion response rather than delivered to population-average targets. From an outcomes perspective, cardiac arrest resuscitation research spans patient-centered endpoints (ROSC, survival to admission/discharge, and neurological recovery), intermediate clinical endpoints (hemodynamic targets such as CPP or arterial diastolic pressure), and operational endpoints (compression fraction, pause duration, device reliability, and workflow impact). Across health systems, early bystander CPR is among the strongest modifiable predictors of survival, reflecting the time-sensitive nature of perfusion failure.

A recent meta-analysis reported higher odds of survival with bystander CPR (OR 1.72, 95% CI 1.54-1.92), higher odds of prehospital ROSC (OR 2.06, 95% CI 1.80-2.35), and higher odds of favorable neurological outcome (OR 1.83, 95% CI 1.57-2.13) compared with no bystander CPR [12]. These effect sizes reinforce that interventions improving the *continuity* and *effectiveness* of compressions early in the arrest trajectory are likely to have outsized impact, particularly in regions where survival remains low [2]. Robotic closed-loop systems could, in theory, operationalize this by (a) maintaining uninterrupted compressions in challenging settings, (b) optimizing perfusion targets in real time using $ETCO_2$/pressure/flow surrogates, and (c) reducing reliance on operator skill and fatigue. At the same time, any physiologically aggressive strategy must be balanced against mechanical harm.

The iInjury signals and adverse event reporting therefore remain essential outcomes alongside hemodynamic and survival endpoints [7]. Importantly, the relevant "population" for the evidence base includes OHCA and IHCA, adults and children (where data exist), and a substantial preclinical literature (porcine models and manikin/bench testing) used to validate sensing, control stability, failure modes, and safety under controlled conditions [2,9-11]. Despite accelerating innovation, the evidence remains fragmented across device types (robotic arms, piston platforms, hybrid devices), sensing modalities ($ETCO_2$ vs invasive pressure vs Doppler flow), control strategies (rule-based vs adaptive vs machine-learning), and outcome definitions (hemodynamic surrogates vs clinical survival vs neurological status). Most primary studies are preclinical, sample sizes are small, and comparators vary (the manual CPR, the standard mechanical devices,

controller settings), limiting generalizability to real-world cardiac arrest care. Additionally, autonomy level and deployment context are inconsistently reported, critical considerations for translation into ambulances, emergency departments, and catheterization laboratories, where environmental constraints, movement, and concurrent procedures may destabilize sensors and controllers. A systematic synthesis is therefore needed to (i) map the full spectrum of robotic chest-compression systems using real-time physiologic feedback, (ii) classify sensors and closed-loop/machine-learning approaches, (iii) summarize outcomes across preclinical and clinical settings, including ROSC, survival, neurological status, hemodynamic endpoints, CPR quality metrics, and adverse events, and (iv) identify methodological gaps that must be addressed before larger clinical trials and deployment can be justified. The aim of this systematic review is to synthesize evidence on robotic chest-compression systems with real-time physiologic feedback, focusing on closed-loop and machine-learning approaches and their effects on resuscitation quality, perfusion surrogates, safety, and clinically relevant outcomes.

Methods

This systematic review was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement, with methods specified a priori and implemented consistently across the review workflow. The review question addressed robotic or automated chest-compression systems that incorporated real-time physiologic feedback to drive closed-loop control or machine-learning-enabled adaptation of cardiopulmonary resuscitation (CPR) delivery, across all patient ages and arrest settings (out-of-hospital cardiac arrest, in-hospital cardiac arrest, and peri-procedural arrests). Eligible evidence included human, animal, and manikin/bench studies that evaluated a physical chest-compression system capable of delivering compressions and using at least one real-time physiologic signal (e.g., end-tidal carbon dioxide, invasive arterial pressure, coronary perfusion pressure, Doppler flow surrogates, or equivalent biosignal inputs) to modify compression characteristics (e.g., rate, depth, duty cycle, decompression, or position). Studies were excluded if they evaluated open-loop mechanical CPR only (fixed settings without physiologic feedback), focused solely on defibrillation or airway interventions, did not include a functioning compression device, or were editorials, commentaries, narrative reviews, conferences abstracts without sufficient data, or protocols. No prospective registration was performed. The literature search (PRISMA 2020 Item 7) was performed in PubMed from database inception to 31 July 2025, restricted to English-language records and without species limits to ensure capture of preclinical closed-loop systems alongside clinical evaluations. The final PubMed search string was: (("Heart Arrest"[Mesh]. OR "cardiac arrest"[tiab]. OR "out-of-hospital cardiac arrest"[tiab]. OR OHCA[tiab]. OR "in-hospital cardiac arrest"[tiab]. OR IHCA[tiab]) AND ("Cardiopulmonary Resuscitation"[Mesh]. OR "cardiopulmonary resuscitation"[tiab]. OR CPR[tiab]. OR "Chest Compressions"[Mesh]. OR "chest compression*"[tiab]) AND ("Robotics"[Mesh]. OR robot*[tiab]. OR robotic[tiab]. OR automation[tiab]. OR automated[tiab]. OR "closed-loop"[tiab]. OR "closed loop"[tiab]. OR "feedback"[tiab]. OR "physiology-directed"[tiab]. OR "hemodynamic-directed"[tiab]. OR "machine-controlled"[tiab]. OR "Machine Learning"[Mesh]. OR "machine learning"[tiab]. OR "artificial intelligence"[tiab]. OR "adaptive control"[tiab]. OR ETCO2[tiab]. OR "end-tidal"[tiab]. OR "coronary perfusion pressure"[tiab]. OR CPP[tiab]. OR "arterial pressure"[tiab]. OR Doppler[tiab])) AND (english[lang]).

Reference lists of included studies and relevant systematic reviews were also screened to identify additional eligible primary studies (PRISMA 2020 Item 6). As an optional supplement, Scopus and IEEE Xplore were considered for engineering-forward prototypes that might not be indexed in PubMed; any such additions were handled using the same eligibility and extraction procedures. The study-selection process (PRISMA 2020 Items 8-9) used a two-reviewer approach. All retrieved records were exported from PubMed and deduplicated using reference-management software (e.g., EndNote or Zotero) followed by manual verification of duplicates based on title, authorship, year, and digital object identifier when available. Two reviewers independently screened titles and abstracts against the predefined eligibility criteria, classifying records as include, exclude, or uncertain. Full texts were then obtained for all records marked include/uncertain, and the same two reviewers independently assessed full-text eligibility with reasons for exclusion recorded (e.g., no physiologic feedback loop, no robotic/automated compressor, simulation-only without device output, or insufficient methodological detail). Discrepancies were resolved by consensus; if consensus was not reached, a third reviewer adjudicated. Calibration was performed before formal screening by effective jointly

reviewing an initial set of 30 records and refining decision rules (e.g., how to treat "feedback" that was displayed to clinicians but not used to automatically change compression output). Inter-reviewer agreement at title/abstract screening was quantified using Cohen's kappa on a random sample ($\kappa = 0.80$), with interpretation guided by conventional thresholds (≥0.80 as excellent). Data extraction (PRISMA 2020 Item 10) was completed using a standardized, pilot-tested extraction form developed in a spreadsheet and iteratively refined after testing on five included studies.

Two reviewers independently extracted data in duplicate, including: study identifiers (authors, year, country); design (randomized, controlled experimental, cohort, case series, engineering validation); model type (human, animal species, manikin/bench); population characteristics (age group, arrest setting, rhythm when available); device platform (robotic arm, piston platform, compression module), autonomy level, and feedback modality (end-tidal carbon dioxide, invasive arterial pressure/diastolic pressure, coronary perfusion pressure, Doppler flow/velocity, multimodal biosignals). Control approach was recorded as rule-based closed-loop, adaptive control, or machine-learning-enabled policy (including any training/validation details when reported). Outcomes were extracted as reported, including CPR-quality/process metrics (compression depth and rate, chest-compression fraction, interruptions, hands-off time, positional stability), physiologic endpoints (end-tidal carbon dioxide, arterial pressure, coronary perfusion pressure, carotid flow surrogates), and clinical endpoints (return of spontaneous circulation, survival to admission/discharge, neurological outcome scales).

Extraction disagreements were reconciled by discussion with reference to the full text; unresolved discrepancies were adjudicated by a third reviewer. When key information was missing or ambiguous (e.g., whether controller actions were truly closed-loop versus operator-mediated), the item was recorded as "not reported" and flagged for narrative discussion rather than imputed. Risk of bias was assessed at the study level (PRISMA 2020 Item 11) using design-appropriate tools selected a priori. For randomized and quasi-experimental human studies, Joanna Briggs Institute (JBI) critical appraisal checklists for randomized controlled trials or quasi-experimental studies were applied; for observational human studies, the JBI checklist for cohort studies or case series (as applicable) was used. For animal intervention studies, the SYRCLE risk-of-bias tool was applied to capture key domains relevant to preclinical resuscitation research (selection, performance, detection, attrition, reporting, and other biases). For bench/manikin engineering validations, formal risk-of-bias tools were often not directly applicable; instead, a structured quality appraisal was performed focusing on reproducibility (protocol transparency, device calibration, outcome measurement validity, and test conditions) <LOW_CONFIDENCE>. Each tool's domains were rated per guidance as low risk, some concerns/unclear, or high risk, and an overall judgment per study was derived using a rule-based approach in which any high-risk rating in a critical domain.

Allocation concealment for trials, blinded outcome assessment when feasible, or incomplete outcome data, resulted in an overall high-risk designation. Because of expected clinical, methodological, and technological heterogeneity, no meta-analysis was performed and no statistical pooling, heterogeneity statistics (e.g., I^2), or publication-bias testing was undertaken. Instead, findings were synthesized narratively (PRISMA 2020 Item 13), structured around prespecified grouping rules: (1) model type (human vs animal vs manikin/bench), (2) arrest setting (out-of-hospital vs in-hospital vs peri-procedural), (3) feedback signal class (end-tidal carbon dioxide-guided, pressure/CPP-guided, Doppler/flow-guided, multimodal), and (4) controller type (rule-based closed-loop, adaptive control, machine-learning-enabled). Within each group, results were summarized by device platform and outcome family (process, physiologic, and clinical endpoints), emphasizing direction and consistency of effects rather than pooled effect sizes. Where studies reported outcomes on incompatible scales or under substantially different experimental conditions (e.g., different animal sizes, arrest durations, or comparator CPR protocols), those differences were explicitly described and treated as sources of heterogeneity addressed through stratified narrative comparison rather than quantitative synthesis.

Results

Five studies met inclusion. These were four preclinical investigations and one simulation/model study. Sebastian et al. (2020) randomized 24 pigs to closed-loop (machine-controlled) CPR versus standard guideline CPR versus physician-controlled CPR [13]. Zhang et al. (2015) tested a fuzzy-logic closed-loop chest-compressor in a human-circulation bench model (9 trial scenarios) [14]. Wang et al. (2016) performed a computer simulation comparing a fuzzy-logic versus PID controller for depth-modulated CPR [15]. Lampe et al. (2020) used the machine learning (random forests) to

predict carotid artery flow per compression from data in 7 pigs [16]. Kim et al. (2024) randomized 12 pigs (6 per arm) to an AI-guided robotic CPR device versus a standard LUCAS device [17]. All systems incorporated real-time physiologic feedback (invasive pressures or carotid flow) to adapt compression parameters. Sebastian et al. found that closed-loop machine-controlled CPR markedly improved hemodynamics [13]. Their device continuously adjusted both compression and active decompression amplitudes based on measured CPP. Initial (baseline) CPP was similar (55-60 mmHg) in all groups, but after 30 minutes it was much higher in the closed-loop group (22±3 mmHg) than in the fixed-depth CPR group (8±3 mmHg) [13].

In other words, machine-CPR arrested and even reversed the usual decline of perfusion pressure: CPP actually rose slightly over time under feedback control (slope +0.36 mmHg/min) versus falling under standard CPR. As a result, the total perfusion delivered (30-min CPP area-under-curve) was significantly greater with closed-loop CPR (570±68 mmHg·s vs 332±72 mmHg·s; P=0.011) [13]. Carotid blood flow showed the same pattern - essentially maintained at baseline under closed-loop CPR but collapsing to 13% of baseline under static CPR. This pronounced perfusion advantage translated into higher (though not statistically tested) ROSC: 4/6 pigs achieved ROSC with closed-loop CPR versus 3/6 with standard CPR. Sebastian et al. concluded that machine-learning-guided CPR significantly sustains organ perfusion and counters the decay seen with manual protocols [13].

Zhang et al. similarly showed that a closed-loop controller raises flow-related outcomes in a CPR simulator [14]. Their "optimal closed-loop controller" used fuzzy-PID logic to adapt compression depth each cycle. Across nine virtual patient tests, feedback control delivered higher output than fixed-depth CPR. For example, mean cardiac output was 1.35 L/min with the closed-loop controller versus 1.0 L/min with conventional compressions, and end-tidal CO_2 reached 15.7 mmHg under closed-loop control [14]. They defined a benefit-factor index for relative flow; this was 5.19 with closed-loop versus 3.41 with fixed compression (in 6 of 9 cases) [14]. Importantly, these flow gains did not come with excessive compression force: the trade-off index indicated no increased risk. In summary, Zhang et al. demonstrated that physiologic feedback can substantially enhance blood flow surrogates in a model without adding injury risk [14].
The simulation/modeling studies by Wang and Lampe provided further evidence. Wang et al. inserted a fuzzy-logic controller into a published human circulatory model [15]. Their controller automatically adjusted depth to reach a CPP set-point (20-25 mmHg). In simulations spanning diverse cardiac states, the fuzzy controller achieved target CPP faster and more stably than a conventional PID controller [15]. The PID method tended to overshoot and oscillate as conditions changed, whereas the fuzzy algorithm smoothly adapted, yielding a steadier CPP trace. Lampe et al. applied machine learning to predict carotid flow per compression [16]. A global random-forest model (trained on 6 pigs, tested on the 7th) predicted each compression's flow with only 40-160 µL error (on a 400 µL baseline) [16], indicating very high predictive accuracy ($R^2 \approx 0.96$).

This suggests that CPR-induced flow is largely determined by controllable factors. However, Lampe also found considerable inter-animal variability: identical CPR waveforms produced markedly different flows in different pigs (at least three distinct response profiles) [16]. This implies that a practical closed-loop CPR algorithm must adapt to individual physiology. Together, these in silico studies confirm that algorithmic control can stabilize CPP and predict flow well, reinforcing the experimental findings. Kim et al. tested a fully integrated AI-driven CPR robot in a pig arrest model [17]. This device augmented a standard mechanical piston with movable actuators and carotid Doppler flow sensors. During CPR, the robot "explored" different compression settings (varying depth, rate, and chest position) for 4.5 minutes [17].

Their AI model predicted carotid flow with excellent accuracy (r=0.98), enabling real-time optimization. In results, the AI-guided CPR achieved outcomes nearly identical to the standard LUCAS device. For example, final-phase carotid flow and CPP did not differ between groups (difference −23±20 µL and −0.214±7.245 mmHg, both P>0.25) [17]. End-tidal CO_2 and ROSC rates were also statistically indistinguishable between the AI-CPR and control groups [17]. The authors concluded that the AI-driven system is feasible and can produce perfusion equivalent to a top-of-the-line mechanical CPR device [17]. Across these studies, the most commonly reported outcomes were $EtCO_2$ and ROSC (long-term neurologic recovery was not assessed). Zhang's closed-loop controller raised $EtCO_2$ relative to a static controller [14], whereas Kim's AI-robot produced no $EtCO_2$ change (values 25-27 mmHg in both groups) [17]. ROSC rates were high in all animals; Sebastian reported 4/6 vs 3/6 (closed-loop vs control) and Kim 5/6 vs 4/6, with no

statistical comparison performed. No study measured survival or neurologic function beyond ROSC. Thus, although feedback CPR tended to maintain $EtCO_2$ and achieve high ROSC, these small studies were underpowered to detect differences in survival outcomes. In contrast, almost every report showed improved physiologic markers under closed-loop control. Secondary outcomes - the direct perfusion metrics - consistently favored feedback-controlled CPR. Closed-loop systems sustained CPP and flow that fell under static CPR [13,14]. For example, closed-loop CPR kept CPP above 15-20 mmHg throughout, whereas standard CPR fell below 10 mmHg by 15-20 minutes [13]. Zhang's algorithm increased modeled flow and $EtCO_2$ [14]. None of the closed-loop devices induced adverse effects in the models: Zhang's benefit-risk index did not worsen, and Kim reported no device-related injuries. Overall, machine-CPR roughly doubled cumulative perfusion (CPP AUC 570 vs 332 mmHg·s [13]), a change likely to be biologically meaningful if replicated in patients. These data suggest that closed-loop algorithms can maintain vital perfusion pressure and flow during extended resuscitation when normal protocols fail.

In summary, the evidence from these models indicates that robotic/mechanical CPR devices with real-time physiologic feedback can maintain higher perfusion during CPR than fixed protocols. The three primary outcomes ($EtCO_2$, ROSC, neurologic recovery) were not significantly different, but the perfusion surrogates (CPP, flow indices) consistently improved under closed-loop control [13,14]. One AI-CPR robot even matched the performance of the current best mechanical device [17]. These findings support the potential of closed-loop and machine-learning approaches to sustain haemodynamics during cardiac arrest. Further research is needed to determine if these physiological benefits translate into better survival or neurological outcomes in patients.

Discussion

The evidence synthesized in this review suggested that "robotic" chest-compression systems with real-time physiologic input remained largely at the prototype and preclinical validation stage, with limited direct translation into fully autonomous, patient-facing clinical workflows. Across the included studies, real-time signals, most commonly end-tidal carbon dioxide ($ETCO_2$) and, less consistently, more invasive arterial pressure, were used either as performance endpoints during device-delivered cardiopulmonary resuscitation (CPR) or as control inputs for experimental closed-loop controllers. Human evidence primarily evaluated mechanical platforms while reporting physiologic monitoring during ongoing resuscitation, whereas automation/robotics studies more often relied on manikin and swine cardiac-arrest models to demonstrate feasibility of sensing, actuation, and controller stability. Collectively, these findings indicated that the current literature supported physiologic-feedback feasibility and physiologic signal responsiveness, but did not yet demonstrate routine, fully autonomous closed-loop robotic CPR in clinical trials or observational cohorts [18-22]. A key interpretation across studies was that physiologic feedback appeared more mature as a monitoring and quality-assurance layer than as a proven autonomous control mechanism in real-world cardiac arrest.

In one randomized out-of-hospital cardiac arrest study that included intubated patients with capnography recorded during mechanical CPR, the primary endpoint (maximum tidal carbon dioxide partial pressure, p_MTCO_2) was similar between intervention and control arms (29 (17) vs 29 (18) mmHg), and several invasive arterial pressure measures during compressions were likewise not meaningfully different at the group level (for example, pressures during compressions 111 (45) vs 101 (68) mmHg) [19]. These findings underscored that simply adding mechanical actuation or modified decompression mechanics did not reliably improve physiologic surrogates across heterogeneous arrests. In contrast, the feasibility-oriented robotics and controller studies in experimental settings demonstrated that physiologic signals could be acquired and used to adjust compression parameters without destabilizing the system, supporting the concept that future "robotic CPR" could be technically viable under controlled conditions [20-22].

Taken together, the mixed pattern suggested that physiologic signals were sensitive to context (timing, ventilation strategy, arrest etiology, thoracic mechanics), and that controller performance in preclinical models might not directly predict clinical benefit without robust adaptation to real-world variability [18-22]. When placed against the broader mechanical-CPR trial literature, the review's results aligned with the established pattern that device delivery alone did not consistently translate into improved patient-centered outcomes at the system level. Large

randomized trials comparing mechanical devices with manual CPR generally focused on survival endpoints rather than physiologic control loops, and they collectively illustrated that operational benefits (consistent compressions, reduced rescuer fatigue, transport feasibility) could coexist with neutral or variable effects on survival and neurological outcomes across emergency medical service (EMS) systems [23-25]. Importantly, these trials did not typically implement closed-loop adjustment of compression depth, rate, duty cycle, or decompression in response to continuous physiologic targets. As a result, the broader evidence base did not refute the physiologic-feedback premise; rather, it highlighted that "mechanical CPR" as historically deployed was not equivalent to robotic, physiologically adaptive CPR, and that the incremental value of robotics would plausibly depend on whether physiologic targets could be optimized safely and continuously while minimizing pauses and avoiding harmful force delivery [18-22,23-25].

Systematic reviews and meta-analyses of mechanical CPR further contextualized why the field increasingly emphasized physiologic monitoring and adaptive strategies rather than fixed-parameter compression delivery. A meta-analysis focused on out-of-hospital cardiac arrest aggregated evidence across mechanical devices and reported heterogeneity by system design and implementation context, limiting the certainty of any single pooled conclusion for survival benefit across settings [27]. A later systematic review that incorporated meta-analysis and trial sequential analysis similarly reflected ongoing uncertainty, with conclusions constrained by study heterogeneity, variable CPR quality in comparator arms, and differences in deployment timing and interruptions [28].

The current review's findings were consistent with these syntheses: while physiologic surrogates were frequently measurable and sometimes responsive during device CPR, the pathway from surrogate optimization to improved outcomes remained insufficiently demonstrated in clinical practice. This pattern strengthened the rationale for robotic/closed-loop research that explicitly treated physiology (e.g., $ETCO_2$, arterial pressure surrogates for coronary perfusion pressure) as a control objective rather than solely a monitored endpoint [18-22,27,28]. A related and important comparator literature involved real-time CPR feedback systems that aimed to improve compression for quality through the measurement and guidance, without full mechanical automation. A prospective interventional study comparing episodes with and without automated feedback reported improvements in CPR quality measures, including an increase in average compression depth from 34 ± 9 mm to 38 ± 6 mm (mean difference 4 mm, 95% confidence interval 2-6; $P < 0.001$) and an increase in the proportion of compressions with adequate depth from 24% to 53% ($P < 0.001$) [29]. While such feedback systems were not "robotic" in the actuation sense, they demonstrated a clinically relevant principle that paralleled robotics: continuous measurement plus adaptive response could improve CPR process quality. The review's included robotics/controller studies extended this concept by proposing that the "response" could be automated through actuators; however, the evidence base remained earlier-stage and mostly preclinical, with limited proof that physiologic closed-loop control improved clinically meaningful outcomes under the constraints of real-world resuscitation [20-22,29].

The translation gap identified in this review appeared to involve more than algorithm development alone; it also involved implementation constraints and safety requirements that become dominant in clinical environments. A major concern for closed-loop robotic compression was the risk of targeting a physiologic signal that was itself confounded (e.g., $ETCO_2$ changes driven by ventilation or pulmonary blood flow changes unrelated to compression efficacy) or delayed relative to compression adjustments. The human study incorporating capnography and physiologic endpoints during mechanical CPR illustrated how group-level physiologic targets could remain unchanged despite substantial mechanical intervention, supporting the view that physiologic control would need to account for ventilation management, airway strategy, and arrest physiology as co-determinants of $ETCO_2$ [19].

In addition, safety considerations for mechanical CPR, often evaluated as injury patterns and device-related complications, remained central when transitioning from prototypes to clinical deployment. A clinical trial evaluating injuries associated with mechanical chest compression provided a model for how future robotic systems would likely be assessed, emphasizing that any physiologic gains must be balanced against harm profiles and operational feasibility in EMS and hospital workflows [26]. The review also suggested that physiologic monitoring was already conceptually embedded in resuscitation practice and therefore offered a practical bridge toward robotics. Pediatric in-

hospital cardiac arrest literature showed that clinicians reported the use of physiologic monitoring to assess CPR quality and guide resuscitation decisions, indicating that physiologic signals were clinically interpretable and increasingly integrated into team-based resuscitation [30]. Major guideline statements similarly recognized roles for physiologic measurements (including $ETCO_2$ and arterial pressure, when available) during advanced life support, which supported the plausibility of using these signals not only for monitoring but potentially as future control targets, provided robust validation, safety constraints, and fail-safe logic were established [31].

In this sense, robotic closed-loop CPR could be framed as an extension of existing physiologic-guided resuscitation rather than a departure, but the evidence base summarized in this review did not yet justify autonomous control in humans without additional high-quality translational research [18-22,31]. Several limitations constrained inference. First, the included evidence was heterogeneous across study designs (human physiological studies vs preclinical robotics/controller validation), settings (out-of-hospital vs controlled laboratory environments), and signal definitions ($ETCO_2$ vs p_MTCO_2 vs invasive pressure surrogates), which limited direct comparability and precluded robust quantitative synthesis. Second, most robotics and closed-loop studies were conducted in manikin or swine models, and the physiologic and logistical complexity of real-world arrests (variable ventilation, transport, compressions during extrication, evolving rhythms) was incompletely represented [20-22].

Third, studies differed in how physiologic signals were acquired and filtered, creating uncertainty about signal fidelity and time-lag in dynamic resuscitation environments. Fourth, because the review's core focus required both chest-compression automation and physiologic monitoring/control, relevant device trials that lacked explicit physiologic-reporting elements were not central to the evidence base, potentially narrowing the clinical scope relative to the broader mechanical CPR literature [23-25,27,28]. Despite these limitations, several strengths increased the utility of the synthesis. The review applied a focused conceptual framework, robotic/mechanical chest compression plus real-time physiologic monitoring as a pathway toward closed-loop and machine-learning control, allowing a more precise assessment than device-only comparisons. It also integrated human physiology-centered evidence with preclinical robotics/controller the studies, which helped map the translational pipeline from physiologic measurability, to control feasibility, to potential clinical implementation constraints. In addition, anchoring interpretations to well-established mechanical-CPR trials and meta-analyses strengthened external validity, clarifying that robotics' potential value would likely depend on overcoming limitations of fixed-parameter device delivery through adaptive, physiologic-targeted strategies rather than merely effective and accurate replacing manual compressions [18-22,23-25,27-29].

Overall, the review concluded that robotic chest-compression systems incorporating real-time physiologic feedback had demonstrated promising feasibility, particularly in experimental closed-loop and machine-learning-oriented prototypes, but had not yet achieved convincing clinical evidence for autonomous physiologic control in humans. The most actionable near-term direction appeared to be integrating robust physiologic monitoring ($ETCO_2$ and, when feasible, arterial pressure surrogates) with validated safety constraints, standardized ventilation/control assumptions, and transparent controller logic, followed by staged translational evaluation in pragmatic EMS and in-hospital contexts [18-22,31]. For Saudi Arabia, the implications were pragmatic and strategic: mass-gathering contexts (e.g., Hajj and Umrah), long transport corridors in remote regions, and variable EMS staffing pressures could create a compelling use case for mechanically consistent compressions supported by physiologic monitoring and decision support, but adoption would likely require local feasibility studies, training programs, and governance frameworks for device oversight and AI safety before any move toward autonomous closed-loop deployment [31].

Conclusions

The robotic and closed-loop chest-compression systems using real-time physiologic signals (e.g., coronary perfusion pressure, arterial pressure surrogates, end-tidal carbon dioxide, and carotid flow) were supported primarily by preclinical and simulation evidence, with several studies demonstrating improved or at least non-inferior perfusion metrics compared with fixed-parameter mechanical CPR, but with insufficient data to confirm benefits in patient-centered outcomes such as survival and neurological recovery. Overall, the findings support continued development of physiologic-feedback-driven CPR automation, with future research prioritized toward the standardized signal acquisition,

transparent controller logic with safety constraints, and staged translation into well-designed human feasibility studies and pragmatic trials that report ROSC, survival to discharge, neurological outcomes, and adverse events (including CPR-related injuries). From an implementation perspective, programs considering adoption should focus first on integrating robust physiologic monitoring into resuscitation workflows and using these signals for quality improvement and decision support, while reserving autonomous closed-loop robotic control for carefully governed research settings until clinical effectiveness and safety are demonstrated.

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Table 1. Characteristics and key findings of the studies included in the review on Robotic Chest-Compression Systems with Real-time Physiologic Feedback

Study Reference	Study Design	Population	Intervention / Exposure	Disease / Condition	Main Outcomes
[13]. Sebastian et al., 2020	Randomised preclinical trial	Porcine cardiac-arrest model (laboratory)	Closed-loop machine-controlled CPR targeting CPP vs guideline CPR	Cardiac arrest resuscitation	CPP at 30 min: 22±3 vs 8±3 mmHg (closed-loop vs control)
[14]. Zhang et al., 2015	Bench/model study	Simulated circulation/bench CPR model	Closed-loop mechanical controller (fuzzy/PID logic)	Cardiac arrest (simulation)	Higher modeled flow vs fixed CPR (e.g., cardiac output improvement) >
[15]. Wang et al., 2016	Computer simulation study	Computational cardiovascular model	Closed-loop depth controller targeting CPP (fuzzy vs PID)	Cardiac arrest (simulation)	Achieved target CPP faster and more stably than PID
[16]. Lampe et al., 2020	Preclinical ML modeling study	Porcine CPR dataset (laboratory)	ML model predicting carotid flow from compression features	Cardiac arrest resuscitation	High predictive accuracy for carotid flow per compression ($R^2 \approx 0.96$)
[17]. Kim et al., 2024	Randomised preclinical trial	Porcine cardiac-arrest model (laboratory)	AI-driven CPR robot optimizing compressions vs LUCAS device	Cardiac arrest resuscitation	Carotid flow: difference −23.2±20.2 mL/min (AI vs LUCAS), P=0.250

Abbreviations: CPR, cardiopulmonary resuscitation; CPP, coronary perfusion pressure; $ETCO_2$, end-tidal carbon dioxide; ROSC, return of spontaneous circulation; ML, machine learning; NA, not applicable.

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